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Technical Analysis and Central Bank Intervention

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TECHNICAL ANALYSIS AND CENTRAL BANK INTERVENTION -- By Christopher Neely and Paul Weller

ABSTRACT --97-002B

This paper extends the genetic programming techniques developed in Neely, Weller and Dittmar (1997) to show that technical trading rules can make use of information about U.S. foreign exchange intervention to improve their out-of-sample profitability for two of four exchange rates. Rules tend to take positions contrary to official intervention and are unusually profitable on days prior to intervention, indicating that intervention is intended to check or reverse predictable trends. Intervention seems to be more successful in checking predictable trends in the out-of-sample (1981-1996) period than in the in-sample (1975-1980) period. We conjecture that this instability in the intervention process prevents more consistent improvement in the excess returns to rules. We find that the improvement in performance results solely from more efficient use of the information in the past exchange rate series rather than from information about contemporaneous intervention.

Technical Analysis and Central Bank Intervention

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Introduction

There is now a considerable amount of evidence to suggest that technical trading rules can earn economically significant excess returns in the foreign exchange market (Dooley and Shafer, 1984; Levich and Thomas, 1993; Neely, Weller and Dittmar, 1997 (henceforth NWD); Neely and Weller, 1998; Sweeney, 1986). But the reasons for the existence of these excess returns are still not well understood. One possible explanation is that the intervention activities of central banks in the market may account for at least part of the profitability of technical trading rules (Dooley and Shafer, 1984; LeBaron, 1998; Szakmary and Mathur, 1997; Neely, 1998). The arguments advanced in favor of this hypothesis focus on the fact that central banks are not profit maximizers, but have other objectives that may make them willing to take losses on their trading. Thus, the stated goal of intervention by the Federal Reserve is to maintain orderly market conditions, and the unstated goals may include the achievement of macroeconomic objectives such as price stability or full employment. If the target for the exchange rate implied by these goals is inconsistent with the market's expectations of future movements in the exchange rate, there may be an opportunity for speculators to profit from the short-run fluctuations introduced (Bhattacharya and Weller, 1997).

LeBaron (1998) investigated the relationship between intervention by the Federal Reserve and returns to a simple moving average trading rule. He used daily intervention data to show that most excess returns were generated on the day before intervention occurred. He found that removing returns on the days prior to U.S. intervention reduced the trading rule excess returns to insignificance. Szakmary and Mathur (1997) examined the link between monthly trading rule returns and monthly changes in the foreign exchange reserves—a proxy for intervention—of five central banks. They also found evidence of an association between intervention activity and trading rule returns.

The fact that trading rule returns were abnormally high on the day *before* intervention tends to support the hypothesis that strong and predictable trends in the foreign exchange market cause intervention, rather than that intervention generates profits for technical traders. But it still leaves open the possibility that a sophisticated technical trader might be able to respond to the fact that intervention had occurred to modify his position and increase his profits. If this is the case, then observing intervention carries additional useful information about the future path of the exchange rate that is not contained in current and past rates.

Thus we are interested in determining whether knowledge of central bank intervention can increase excess returns to trading rules in dollar exchange rate markets. We investigate this question using the methodology developed in NWD (1997). This allows us to identify optimal ex ante trading rules that use information about whether intervention has occurred, and to compare their profitability to that of rules obtained without the use of such information. We find substantial differences between in-sample and out-of-sample periods, suggesting that the effects of intervention have not been stable over time. We also find strong evidence for two currencies (British pound and Swiss franc) that the use of in-sample intervention data improves the efficiency with which trading rules use information in the past exchange rate series.

1. Methodology

We use genetic programming as a search procedure to identify trading rules that use information both on the past exchange rate series and on intervention activity. We have previously used this technique to find profitable rules that use data on exchange rates alone (NWD, 1997) and exchange rates and interest rates (Neely and Weller, 1998). It has also been applied in the equity market (Allen and Karjalainen, 1998). The method is particularly useful for our purposes as it permits flexible incorporation of additional information on central bank intervention into the trading rule.

The genetic program operates by creating successive populations of trading rules according to certain well-defined procedures. Profitable rules are more likely to have their components reproduced in subsequent populations. The basic features of the genetic program are: (a) a means of encoding trading rules so that they can be built up from separate subcomponents; (b) a measure of profitability or "fitness"; (c) an operation which splits and recombines existing rules in order to create new rules.

Before we describe these features, let us first introduce some notation. The exchange rate at date t (USD per unit of foreign currency) is given by S_t. Intervention at date t is given by the indicator variable, I_t, which can take on values 1, 2, or 3, according to whether the U.S. authorities buy dollars, do not intervene, or sell dollars respectively at date t. A trading rule can be thought of as a mapping from past exchange rates and intervention data to a binary variable, z_t, which takes the value +1 for a long position in foreign exchange at time t, and -1 for a short position. Trading rules may be represented as trees, whose nodes consist of various mathematical functions, logical operators and constants. Examples of some of the functions used are "average", "max", "min", and "lag". The functions are distinguished by the data series on which they operate. Thus $\max_S(k)$ is equivalent to $\max(S_{t-1}, S_{t-2}, ..., S_{t-k})$, and $\text{lag}_I(k)$ is equal to I_{t-k}. Logical operators include "and", "or", "not", "if-then" and "if-then-else".

Figure 1 presents an example of a simple trading rule that makes use of both exchange rate and intervention data. It signals a long position in foreign currency at date t if the 15-day moving average is greater than the 250-day moving average, or if the U.S. authorities intervened to buy dollars in the last two days, otherwise a short position.

The fitness criterion we use in the genetic program is the excess return to a fully margined long or short position in the foreign currency. The continuously compounded (log) excess overnight return is given by $z_t r_t$ where z_t is the indicator variable described above, and r_t is defined as:

$$r_t = \ln S_{t+1} - \ln S_t + \ln(1 + i_t^*) - \ln(1 + i_t) .$$

(1)

The domestic (foreign) overnight interest rate is i_t (i_t^*). The cumulative excess return from two round-trip trades[1] (go long at date t, go short at date $t + k$), with round-trip proportional transaction cost c, is

$$r_{t,t+k} = \sum_{i=0}^{k-1} r_{t+i} + \ln(1 - c) - \ln(1 + c)$$

(2)

Therefore the cumulative excess return r for a trading rule giving signal z_t at time t over the period from time zero to time T is:

[1] Each trade incurs a round-trip transaction cost because it involves closing a long (short) position and opening a short (long) one.

$$r = \sum_{t=0}^{T-1} z_t r_t + \frac{n}{2}\ln\left(\frac{1-c}{1+c}\right).$$

(3)

where n is the number of trades. This measures the fitness of the rule.

To implement the genetic programming procedures we define 3 separate subsamples, the training, selection and validation periods. The first two periods are equivalent to an in-sample estimation period. The third, the validation period, is used to test the rules trained and selected in the first two periods. The results from this period therefore constitute a true out-of-sample test of the performance of the rules. The distinct time periods for all currencies were chosen as follows: training period, 1975-1977; selection period, 1978-1980; validation period, 1981-1996.

The separate steps involved in implementing the genetic program are described below.

Step 1. Create an initial *generation* of 500 randomly generated rules.

Step 2. Measure the *excess return* of each rule over the *training period* and rank according to excess return.

Step 3. Select the highest ranked rule and calculate its excess return over the *selection period*. If this rule generates a positive excess return, save it as the initial *best rule*. Otherwise, designate the no-trade rule as the initial best rule, with zero excess return.

Step 4. Select two rules at random from the initial generation, using weights attaching higher probability to more highly-ranked rules. Apply the recombination operator to create a new rule, which then replaces an old rule, chosen using weights attaching higher probability to less highly-ranked rules. Repeat this procedure 500 times to create a new generation of rules.

Step 5. Measure the fitness of each rule in the new generation over the training period. Take the best rule in the training period and measure its fitness over the selection period. If this best-of-generation rule outperforms the previous best rule, save it as the new best rule.

Step 6. Return to step 4 and repeat until we have produced 50 generations or until no new best rule appears for 25 generations.

The stages above describe one *trial*. Each trial produces one rule whose performance is assessed by running it over the validation period from 1981-1996. Figure 2 illustrates the splitting and recombination operation referred to in Step 4. A pair of rules is selected at random from a population, with a probability weighted in favor of rules with higher fitness. Then subtrees of the two parent rules are selected randomly. One of the selected subtrees is discarded, and replaced by the other subtree, to produce the offspring rule.[2]

The round-trip transaction cost *c* was set to 0.0005 (5 basis points) in the validation period to reflect accurately the costs to a large institutional trader.[3] In the training and selection periods, however, we treat *c* as a parameter in the search algorithm and set it equal to 0.001 to bias the search in favor of rules that trade less frequently. We have shown in NWD (1997) that this is an effective way of reducing the chances of overfitting the data.

[2] The operation is carried out subject to the requirement that the resulting rule must be well-defined. We also impose a restriction that a rule may not exceed a specified size (10 levels and 100 nodes).

2. The Data

We use the noon (New York time) buying rates for the German mark, yen, pound sterling and Swiss franc (USD/DEM, USD/JPY, USD/GBP, and USD/CHF) from the H.10 Federal Reserve Statistical Release. Daily interest rate data are from the Bank of International Settlements (BIS), collected at 9:00am GMT (4:00am, New York time).

As in NWD (1997), we normalize the exchange rate data by dividing by a 250-day moving average. The intervention data we use is the "in market" series from the Federal Reserve Board aggregated across all currencies. The "in market" transactions are explicitly conducted to influence the exchange rate. We construct a variable that can take on one of three values, 1, 2 or 3, depending on whether the U.S. authorities bought dollars, did not transact, or sold dollars on a particular day.

Table 1 presents some summary statistics for the various exchange rate returns, including the interest differential but excluding interest accruing over weekends and other missing observations. There is little evidence of significant skewness, and all return series are strongly leptokurtic. Table 2 provides summary statistics on U.S. intervention. We see that the frequency of intervention has declined dramatically over time. Dollar purchases were seven times more frequent during the selection period than the validation period. This partly reflects the fact that from 1981 to 1985 there was very little intervention by the United States.[4] There has also been relatively little intervention during the Clinton administration. At the same time the mean size of intervention has increased by a similar order of magnitude. The average dollar purchase was eleven times greater in the

[3] NWD (1997) discuss estimates of transaction costs.

[4] This was the result of a conscious policy decision by the Reagan administration (see the introduction to Edison (1993)).

validation period than in the training period. In Table 3 we show the breakdown of intervention in different currencies over the different sample periods. The DEM has been the dominant intervention currency throughout the sample period, but the JPY is much more commonly used during the validation period. Although there were no JPY interventions at all during the training period, the currency accounted for 45 per cent of intervention volume during the validation period. There is a correspondingly sharp decline in the volume of intervention in other currencies during this period.

3. Results

3.1 Granger Causality

To provide a benchmark against which to interpret our results, we first analyze two two-variable vector autoregressions run on the full sample of data from 1981 to 1996. The first includes the exchange rate return and the quantity of intervention by the Federal Reserve, and the second substitutes for the simple return the squared exchange rate return as a measure of volatility. The Akaike information criterion selected 16-23 lags for each of the eight systems. The p-values reported in Table 4 indicate the probability that we would obtain at least as extreme a test statistic if there were no Granger causality. Thus a low p-value provides support for the presence of causality. There is very strong evidence that returns and squared returns (except for the JPY) help predict intervention and also support for the hypothesis that intervention causes returns.

If intervention is a predictor of future exchange rate returns, then observing whether intervention has occurred may be valuable information for foreign exchange traders. However, it is important to emphasize that the evidence that intervention has power to predict returns does not necessarily imply that a trading strategy that conditions on intervention will be more profitable than one that does not. There are several reasons for this. First, Granger causality tests identify relationships of linear predictability, whereas the genetic programming procedure is not constrained in the same way. Thus the predictive power attributed to intervention by the Granger causality tests may also be present as a non-linear component in the past exchange rate return series. This component may already have already been incorporated into the trading rules trained only on exchange rate data. Second, the causality tests use the magnitude of intervention, which is not observed by traders in the market at the time of intervention. In contrast we provide the genetic program with information only about whether the Federal Reserve intervened on a particular day, and if so, on what side of the market. Third, evidence of causality provides no indication of the economic significance of the relationship. In particular, transactions costs may eliminate any potential increase in profitability.

3.2 Performance Comparisons

We have already shown in our earlier paper (NWD, 1997) that trading rules identified by genetic programming and based only on past observations of the exchange rates earn significant excess returns in the out-of-sample period. Here we compare the performance of trading rules trained only on exchange rate data with rules trained on both exchange rate and intervention data.[5] We run 200 trials for each currency, 100 with

[5] In NWD (1997) we used exchange rate data from DRI. In an earlier version of this paper we used DRI data, but later discovered that the time of collection of the data had been incorrectly documented by DRI. In fact, the time at which the data were collected changes in mid-sample. Prior to October 8 1986 the time of collection was 9:00am New York time (the New York open), and after that 11:00 New York time (the London close). Since the vast majority of intervention is timed to occur within the window bracketed by these two times, the information set for traders at date t changes in a crucial way. This is

intervention data and 100 without. This generates a set of 100 rules for each currency under each informational scenario. We adopt this approach because the output from a genetic program is inherently stochastic. Although successful rules should detect similar predictive patterns in the data, there is generally some variation in the structure of rules generated from distinct trials. We therefore need a large enough sample of rules to produce a reliable estimate of the average difference in excess return.

The results of the comparison are displayed in Table 5. The mean improvement in excess return over all currencies is 0.68 per cent per annum. But no consistent pattern emerges. The return to the CHF rules improves by 3.1 per cent and to the GBP by 1.1 per cent. But returns for the DEM and JPY are adversely affected. The improvement in performance for the CHF is accompanied by an increase in the number of rules producing a positive excess return from 49 to 89. It is also clear that the information on intervention is being incorporated into the trading rules, as indicated by the substantial changes in trading frequency and proportion of time spent in a long position. We present further evidence on this issue below.

Although the information presented in Table 5 is a useful way of summarizing the performance of the trading rules, it does not accurately reflect the returns that a trader would have earned from the use of these rules. Even if a trader had chosen to attach a weight of 1/100 to each individual rule, the mean return understates the return to this composite rule by double counting some transaction costs. We consider two alternative ways of aggregating the information contained in the individual rules into a composite

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important, since as Peiers (1997) has shown, there are significant information asymmetries around the time of intervention, which in her study of Bundesbank interventions, did not get resolved until shortly before a Reuters report. Not surprisingly, trading rule: the *uniform portfolio rule* and the *median portfolio rule*. The uniform portfolio rule allocates a fraction 1/100 of the value of the portfolio to each rule.[6] The median portfolio rule generates a long signal at date *t* if 50 per cent or more of the rules give a long signal at date *t*. Otherwise it gives a short signal. The performance of the uniform and median portfolio rules with and without intervention information is presented in Table 6.

As might be expected from Table 5, the effects of supplying information on intervention are mixed. In the case of the CHF there is a very substantial improvement in the performance of both uniform and median portfolio rules. The return to the uniform rule rises from 1.35 per cent to 4.19 per cent, and the return to the median rule rises from –0.13 per cent to 5.36 per cent. There is also considerable improvement in the performance of rules for the GBP, where the median portfolio return rises by 3.66 per cent. But excess returns are adversely affected in the case of the DEM and JPY.

To test the significance of the difference between the portfolio rule returns with and without intervention information, we report Bayesian posterior probabilities. A probability greater than 0.5 means that the evidence favors the hypothesis that excess returns are higher when intervention information is used. Strong evidence of an improvement in performance exists for the CHF and GBP. However, there is also strong evidence that the median rules for the DEM and JPY did less well with intervention data than without.

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the results with the DRI data set exaggerated the impact of intervention information on trading rule profitability.

[6] The excess return to the uniform rule coincides exactly with the mean excess return when transaction costs are zero. Because a simple averaging procedure results in some

3.3 How is the Intervention Data Used?

We conduct two experiments in order to illuminate the way in which the information on intervention influences the performance of the rules. First we compute returns to the rules that are trained with intervention data but are then supplied with a fictitious series out-of-sample indicating that intervention is always zero. Comparing Panel A of Table 7 with the results in Table 5 we see that performance actually improves for the DEM and CHF, and is essentially unaffected for the JPY and GBP. This is an indication that there has been a change in the response of the exchange rate to intervention between in-sample and out-of-sample periods. It also demonstrates that for the GBP and CHF, the two currencies where intervention information improved performance, all the value of training rules with intervention data comes from more efficient use of the information contained in the past exchange rate series alone. The intervention signal, by changing the structure of the rules, is able to filter out the impact of intervention.

Next we perform the following simulation experiment. We assume that a simple Markov switching model generates the intervention series independently of the return series. We generate 100 simulated intervention series using the transition probabilities estimated from the validation period and run each set of 100 rules on the observed exchange rate data and the simulated intervention series. This procedure eliminates any predictive power that intervention might have had for future exchange rate returns. In Panel B of Table 7 we report the performance of each set of rules. All four rules perform

double counting of transaction costs, the uniform portfolio rule return will always be at least as great as the mean return.

more poorly, and average excess return falls by 0.93 per cent when compared to the figures in Table 5. There is also a substantial increase in trading frequency. Evidently the simulation procedure has eliminated features of the joint distribution of intervention and exchange rate returns that had been incorporated into the trading rules.

The most direct method for determining how the genetic programming rules use the central bank intervention data is to analyze the structure of individual rules. But this approach is generally informative only when the structure of the rule to be analyzed is fairly simple. Although such rules may not be representative of the total population, it is interesting to examine an example of a simple rule produced for the CHF. The rule, illustrated in Figure 3, had a mean annual excess return of 4.48 per cent per annum over the out-of-sample period, and a correlation of 98.53 per cent with the median portfolio rule. It provides a clear illustration of the way in which intervention information influences the signal. The rule instructs "Take a long position in foreign currency if the normalized exchange rate is greater than the norm (absolute value of the difference) of the maximum value of the intervention variable (over a time window determined by current intervention) and the normalized exchange rate." The price normalization (division by a 250-day moving average) means that the exchange rate series moves fairly closely around unity. So on a date when the Federal Reserve buys dollars ($I = 1$) the rule will always signal a long position in foreign currency, and conversely on a day when it sells dollars ($I = 3$) the rule will always signal a short position. Otherwise the rule takes a form that is essentially equivalent to "Take a long position in foreign currency if the current value of the exchange rate is greater than its 250-day moving average".

3.4 Trading Rule Returns around Intervention

We next turn to investigating the performance of the trading rules around days when intervention took place, concentrating on the median portfolio rules. In Panel A of Table 8 we present for the USD/DEM the annualized daily percentage return over the period 1981-1996, conditioned on intervention by the U.S. authorities at time t. There is an immediately striking feature to these figures. The excess return at $t-1$, i.e. the return from date $t-1$ to date t, is very much larger than the returns on the subsequent two days when the Fed is in the market.[7] This explains why the return at $t-1$ conditional on no intervention at t is significantly lower than the unconditional mean return. Many of the largest returns to the trading rule are excluded. Notice also that the intervention that occurs at date t is on the *opposite* side of the market from that taken by the trading rule. The portfolio rule tends to be long in foreign currency at $t-1$ when there is a large depreciation of the dollar from $t-1$ to t, and this depreciation is associated with *purchases* of dollars by the Federal Reserve. This clearly supports the hypothesis that the Federal Reserve intervenes to check a strong and predictable trend in the exchange rate. Consistent with results found by Humpage (1998) the figures in the table indicate that at least over a very short horizon the action is successful during the period 1981-96. From the top row we see that if the Federal Reserve intervened and bought dollars at date t, the return to the median portfolio rule from t to $t+2$ was –29 per cent. Since the great majority of individual rules took a long position in foreign currency, this indicates on average an appreciation of the dollar on this date. A similar picture emerges for dollar

[7] These results are consistent with LeBaron (1998), who found that removing returns on days prior to non-zero intervention reduced the profitability of a simple moving average

sales. The return to the USD/DEM rule was 87 per cent at $t - 1$, and – 14 per cent over the subsequent two trading days.

In Panel B we present the same calculations for the period 1975-1980.[8] The pattern of returns is rather different. Returns to trading rules taking the opposite side of the market continue to be positive on the day following an intervention. This indicates that there was a change in the response of the exchange rate to intervention between in-sample and out-of-sample periods. It is clear that the DEM trading rules correctly identified a profitable reaction to intervention over the period 1975-1980. However, this reaction was no longer profitable over the period 1981-1996. This change in the impact of intervention provides us with an explanation for the somewhat poorer out-of-sample performance of the trading rules using intervention information compared to those using only exchange rate information.

We see the same effect at work in the case of the CHF and GBP in Tables 9 and 10. It is striking that here despite the altered reaction of the exchange rate to intervention in the out-of-sample period, training with intervention data still produced an overall improvement in performance. The results for the JPY are not informative because the median portfolio rule, trained with intervention information, performed poorly out of sample and took long positions over 99 per cent of the time. We therefore omit them.

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trading rule to insignificance. Note that LeBaron's study used data from DRI and that the time at which these data were collected changed in mid-sample (see footnote 5).

[8] In the in-sample calculations in Tables 8 through 10, we use the same transactions cost, 5 basis points per round trip, as we do in the out-of-sample calculations.

4. Discussion and Conclusion

There is a sharp difference between the results we find for the major intervention currencies DEM and JPY, and the other two currencies we examine, the GBP and CHF. For both DEM and JPY, providing intervention information leads to some deterioration in performance during the out-of-sample period 1981-1996. The evidence suggests that this is a consequence of a change in the response of the exchange rate to intervention by the Federal Reserve. During the in-sample period from 1975 to 1980, intervention, although it succeeds in slowing the movement in the exchange rate, does not immediately reverse it. Trading rules correctly interpret the intervention signal as an indication that the current trend in the exchange rate will persist, at least over the day following intervention. This interpretation is no longer true during the out-of-sample period from 1981 to 1996. On average there is a sharp reversal in trend conditional on intervention. It seems reasonable to suppose that this increase in the short-term effectiveness of intervention is a consequence of the marked policy shift illustrated in Table 2. Interventions during the out-of-sample period are both much larger and much less frequent.

However, in the case of the GBP and CHF, excess return increases as a result of training with intervention data, by over three percentage points per annum in the latter case. This comes about not because the intervention signal itself has predictive power out-of-sample, but because the predictive component in the past exchange rate series alone is better identified. What this indicates is that intervention adds more noise to the past series of these two currencies. It is likely that this can be attributed to lower liquidity in these markets. This interpretation is supported by the fact that the greatest improvement in performance is observed in the least liquid market, that for the CHF. For this currency too we see by far the largest increase in the proportion of rules generating a positive excess return, from 49 to 89.

These findings raise a number of questions for further research. They suggest that the advantageous impact of training rules with intervention data should be observable in other less liquid currency markets. In addition, since the benefits result from filtering out the noise in the exchange rate caused by intervention, it is possible that some further improvement in performance might accrue to the use of quantitative intervention information. We deliberately chose not to use quantitative information in this study in order to be able to investigate the potential out-of-sample benefits to conditioning on intervention. Also, given the evidence that the response to intervention has been fairly consistent over the period 1981-1996, it is possible that an analysis using more recent training and selection periods would show some out-of-sample benefit to conditioning on intervention.

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Table 1

Summary statistics: Daily exchange rate returns including interest differential but excluding weekends and missing observations: 1975-1996

	DEM	*JPY*	*GBP*	*CHF*
Observations	5417	5439	5386	5418
Mean*100	0.0035	0.0134	0.0007	0.0012
SD*100	0.67	0.63	0.65	0.77
Skewness	-0.07	0.43	-0.12	-0.01
Kurtosis	3.55	4.05	3.69	3.21
Min*100	-5.89	-3.56	-3.86	-5.85
Max*100	4.13	5.15	4.60	4.39

The kurtosis and skewness statistics are marginally distributed as standard normals under the null hypothesis that the distribution is normal. See Kendall and Stuart (1958) for a derivation of these statistics.

Table 2

Summary statistics on US intervention data: "in market" series: 1975-1996

	training	*selection*	*validation*	*overall*
Observations	735	741	3964	5440
% > 0	18.10	26.45	3.58	8.66
% < 0	18.37	22.67	5.35	9.47
Mean > 0 (million)	20.38	136.61	228.42	131.47
Mean < 0 (million)	-9.62	-57.80	-169.63	-91.21
SD > 0	20.42	146.60	297.22	204.65
SD < 0	7.73	77.45	162.68	132.20
Min	-46	-379	-1250	-1250
Max	112	905	1600	1600

The data subsamples are: training period 1975:1–1977:12; selection period 1978:1–1980:12; validation period 1981:1–1996:12. Positive intervention corresponds to purchases of dollars. These figures are for the series matched to the USD/JPY exchange rate series. Because each exchange rate series has different missing values, there will be small differences for the intervention series matched to other exchange rate data.

Table 3

Proportion of intervention in different currencies: 1975 – 1996

	DEM	*JPY*	*Other*
Training	86.17	0.00	13.83
Selection	92.19	1.92	5.89
Validation	53.96	44.95	1.08
Overall	67.90	28.94	3.16

Each column gives the proportion of absolute intervention in different currencies from the "in market" series provided by the Federal Reserve.

Table 4

Granger-causality tests: p-values for the null hypothesis that there exists no causality

	DEM	*JPY*	*GBP*	*CHF*
Intervention causes returns	0.0016	0.0105	0.0423	0.0032
Returns cause intervention	0.0000	0.0000	0.0000	0.0000
Intervention causes squared. returns	0.5845	0.0949	0.7481	0.0618
Squared. returns cause intervention	0.0115	0.1230	0.0938	0.0001
R^2 for intervention causing returns	0.0151	0.0163	0.0204	0.0188
R^2 for returns causing intervention	0.1904	0.1948	0.1938	0.1973
R^2 for intervention causing squared returns	0.0631	0.0442	0.0814	0.0599
R^2 for squared returns causing intervention	0.1903	0.1884	0.1886	0.1955

This table presents results from estimating two two-variable VARs using total U.S. foreign exchange intervention in millions of dollars and either the exchange rate return or squared return inclusive of interest differentials over the period 1981-1996, excluding weekends. Low p-values in the first four rows indicate that we reject the null of no Granger causality.

Table 5

Mean annual trading rule excess return for each currency over the period 1981-96; Rules using intervention information vs. rules not using intervention information

		DEM	*JPY*	*GBP*	*CHF*
AR*100	CBI	5.93	3.43	3.74	4.14
	No CBI	6.26	4.59	2.63	1.05
Sharpe ratio	CBI	0.51	0.29	0.31	0.32
	No CBI	0.53	0.40	0.21	0.08
Trades per year	CBI	9.90	4.86	9.40	10.35
	No CBI	5.45	8.91	8.45	13.68
% long	CBI	47.14	81.19	56.19	52.90
	No CBI	47.88	65.34	65.70	77.20
# rules > 0	CBI	98	93	97	89
	No CBI	99	86	96	49
Long return		0.27	1.39	0.04	-1.27

The rows denoted CBI show results for the rules that use central bank intervention data. The rows denoted No CBI show results for the rules identified only from exchange rate data, as in NWD (1997). There will be some discrepancies between the figures reported here for the No CBI rules and those in NWD (1997) because we have used a different data set for the reasons given in footnote 5. We have also used a slightly extended out-of-sample period in the present study. The annual percentage rate of return is calculated over the first 100 rules that produced nonnegative excess returns in the selection period. The Sharpe ratio is the annual mean excess return divided by the annual standard deviation of the excess return. Trades per year gives the average annual number of trades made over the period 1981-1996, averaged over each set of 100 rules. % long is the percentage of the time the rule was long in the foreign (non-dollar) currency. The "# rules > 0" is the number of the 100 rules with positive mean validation period returns. The long return is the mean annual return to a long position in the foreign (non-US) currency.

Table 6

Portfolio trading rule excess return for each currency over the period 1981-1996
Rules using intervention information vs. rules not using intervention information

Panel A: Uniform portfolio

		DEM	*JPY*	*GBP*	*CHF*
AR*100	CBI	5.98	3.49	3.89	4.19
	No CBI	6.33	4.71	2.72	1.35
t-statistic	CBI	2.24	1.75	1.82	1.49
	No CBI	2.51	2.64	1.19	0.67
Posterior prob.		34.00	13.20	92.40	85.40
Sharpe ratio	CBI	0.55	0.39	0.41	0.36
	No CBI	0.61	0.60	0.27	0.17
Trades per year	CBI	9.01	3.85	6.63	9.58
	No CBI	4.07	6.50	6.68	7.84
% long	CBI	47.15	81.20	56.18	52.91
	No CBI	47.89	65.35	65.70	77.20

Panel B: Median portfolio

		DEM	*JPY*	*GBP*	*CHF*
AR*100	CBI	6.29	1.13	4.83	5.36
	No CBI	7.45	6.45	1.17	-0.13
t-statistic	CBI	2.18	0.42	1.68	1.68
	No CBI	2.58	2.42	0.40	0.04
Posterior prob.		9.10	3.40	96.10	90.50
Sharpe ratio	CBI	0.54	0.09	0.36	0.41
	No CBI	0.63	0.57	0.09	-0.01
Trades per year	CBI	8.50	2.12	4.87	7.87
	No CBI	2.12	3.94	5.62	3.62
% long	CBI	45.72	99.26	49.73	48.87
	No CBI	45.52	62.46	69.46	98.70

The rows denoted CBI show results for the rules that use central bank intervention data. The rows denoted No CBI show results for the rules identified only from exchange rate data. AR*100 is the mean annual return over the validation period for the 100 rules. The table shows the Newey-West corrected t-statistic for the null hypothesis that each portfolio rule has a return equal to zero. Posterior prob. is the Bayesian posterior probability that the excess return of the portfolio using intervention information is greater than that of the rule that does not use such information. The Sharpe ratio is the annual mean excess return divided by the annual standard deviation of the excess return. Trades per year for the uniform portfolio normalizes by the fraction of the portfolio traded. % long is the percentage of the time the rule was long in the foreign (non-dollar) currency. For the uniform portfolio this represents an average over all individual rules.

Table 7

Mean annual excess returns over the period 1981-96 for the trading rules run on actual exchange rate data and fictitious intervention data

Panel A: null intervention signal

	DEM	*JPY*	*GBP*	*CHF*
AR*100	6.31	3.42	3.63	5.00
Sharpe ratio	0.53	0.29	0.30	0.38
Trades per year	3.78	2.84	8.90	5.32
% long	47.57	81.28	55.90	53.90
# rules > 0	98	93	94	89

Panel B: simulated intervention signal

	DEM	*JPY*	*GBP*	*CHF*
AR*100	4.27	2.77	3.60	2.88
Sharpe ratio	0.37	0.24	0.30	0.22
Trades per year	23.96	8.17	10.54	25.28
% long	47.59	83.35	55.55	51.60
# rules > 0	96	93	98	89

Panel A shows the results, comparable to those in Table 5, if the rules are provided with fictitious intervention data during the validation period in which all intervention data is set to zero. Panel B displays the mean results from drawing 100 sets of intervention data from a calibrated Markov switching process. Line 1 of each panel of the table gives the annual per cent excess return averaged over all 100 rules provided with the intervention series during training and selection periods. Line 2 gives the average Sharpe ratio. Line 3 lists the average number of trades per year over the validation period, and line 4 indicates the average proportion of days during the test period on which the rules gave a long signal. The number of rules that generated a positive excess return is given in line 5.

Table 8

Median portfolio returns and positions conditional on intervention/no intervention by the U.S. Authorities: USD/DEM

Panel A: Out-of-sample results 1981-1996

	t - 1	*t*	*t + 1*
AR*100 (Fed buys USD)	47.71	-6.28	-22.26
MSD*100	6.80	4.17	1.49
% long DEM	80.99	100.00	84.51
AR*100 (Fed sells USD)	87.03	-10.88	-3.23
MSD*100	5.27	3.69	1.90
% long DEM	11.01	0.46	10.09
AR*100 (Fed out)	2.09	7.30	7.41
MSD*100	3.20	3.31	3.32
% long DEM	46.20	46.11	46.14

Panel B: In-sample results: 1975 – 1980

	t - 1	*t*	*t + 1*
AR*100 (Fed buys USD)	58.30	20.43	-9.32
MSD*100	4.26	2.17	3.78
% long DEM	87.37	100.00	90.53
AR*100 (Fed sells USD)	37.35	11.61	5.96
MSD*100	5.56	1.58	2.01
% long DEM	34.87	0.00	26.89
AR*100 (Fed out)	-6.05	5.88	12.78
MSD*100	1.45	2.07	2.13
% long DEM	66.55	69.82	67.25

Line 1 of each panel gives the per cent return conditional on intervention at date *t* to buy dollars. The first figure in the column headed *t* - 1 gives the return from the rate collected at 12:00 noon New York time on date *t* - 1 to the rate collected at the same time on date *t*. The figures for the succeeding columns are interpreted similarly. Line 2 reports the monthly standard deviation of median portfolio returns on the date specified. Line 3 reports the percent of observations involving a long position in DEM for the median portfolio rule. Lines 4-6 and 7-9 report figures conditional on intervention to sell dollars at date *t*, and on no intervention at date *t* respectively.

Table 9

Median portfolio returns and positions conditional on intervention/no intervention by the U.S. Authorities: USD/CHF

Panel A: Out-of-sample results 1981-1996

	t - 1	*t*	*t + 1*
AR*100 (Fed buys USD)	45.80	-10.93	-16.25
MSD*100	7.58	3.55	0.59
% long CHF	85.21	100.00	89.44
AR*100 (Fed sells USD)	89.18	-2.48	-22.37
MSD*100	4.49	4.29	2.34
% long CHF	6.88	0.00	0.46
AR*100 (Fed out)	1.05	6.10	7.03
MSD*100	3.68	3.89	3.93
% long CHF	49.61	49.49	49.75

Panel B: In-sample results: 1975 – 1980

	t - 1	*t*	*t + 1*
AR*100 (Fed buys USD)	65.44	24.11	0.53
MSD*100	7.74	2.85	4.12
% long CHF	81.05	100.00	89.12
AR*100 (Fed sells USD)	25.99	14.12	14.66
MSD*100	7.24	2.17	2.82
% long CHF	24.37	0.00	4.62
AR*100 (Fed out)	-10.70	-0.39	4.23
MSD*100	2.96	3.13	3.38
% long CHF	62.67	62.91	64.36

See Table 8 for explanation.

Table 10

Median portfolio returns and positions conditional on intervention/no intervention by the U.S. Authorities: USD/GBP

Panel A: Out-of-sample results 1981-1996

	t - 1	*t*	*t + 1*
AR*100 (Fed buys USD)	93.47	9.26	-29.38
MSD*100	3.39	3.16	1.90
% long GBP	86.62	86.62	85.92
AR*100 (Fed sells USD)	32.43	-27.89	-7.95
MSD*100	5.50	2.85	2.27
% long GBP	38.99	38.07	37.16
AR*100 (Fed out)	1.35	6.02	6.23
MSD*100	3.52	3.56	3.69
% long GBP	49.19	49.23	49.28

Panel B: In-sample results: 1975 – 1980

	t - 1	*t*	*t + 1*
AR*100 (Fed buys USD)	72.71	21.79	2.91
MSD*100	4.42	2.69	3.48
% long GBP	86.67	86.67	86.67
AR*100 (Fed sells USD)	-7.86	7.49	-3.38
MSD*100	5.35	1.88	1.14
% long GBP	78.15	78.15	77.73
AR*100 (Fed out)	-0.29	7.35	13.01
MSD*100	2.31	2.55	2.78
% long GBP	66.06	66.08	66.20

See Table 8 for explanation.

Figure 1 An example of a trading rule

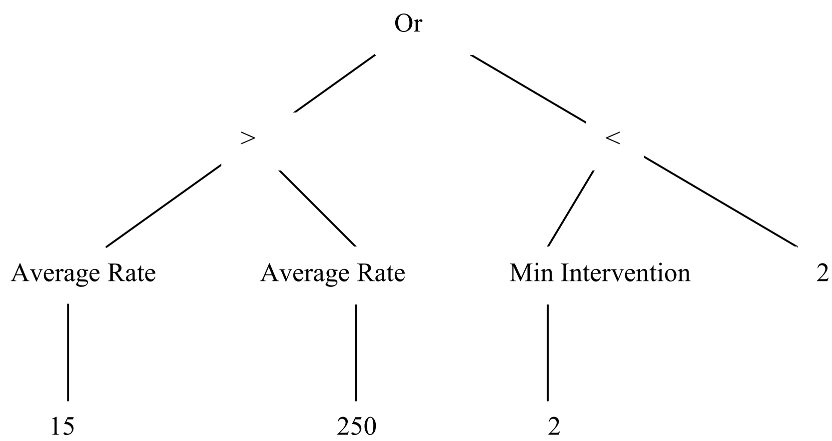


Figure 2 The recombination operation

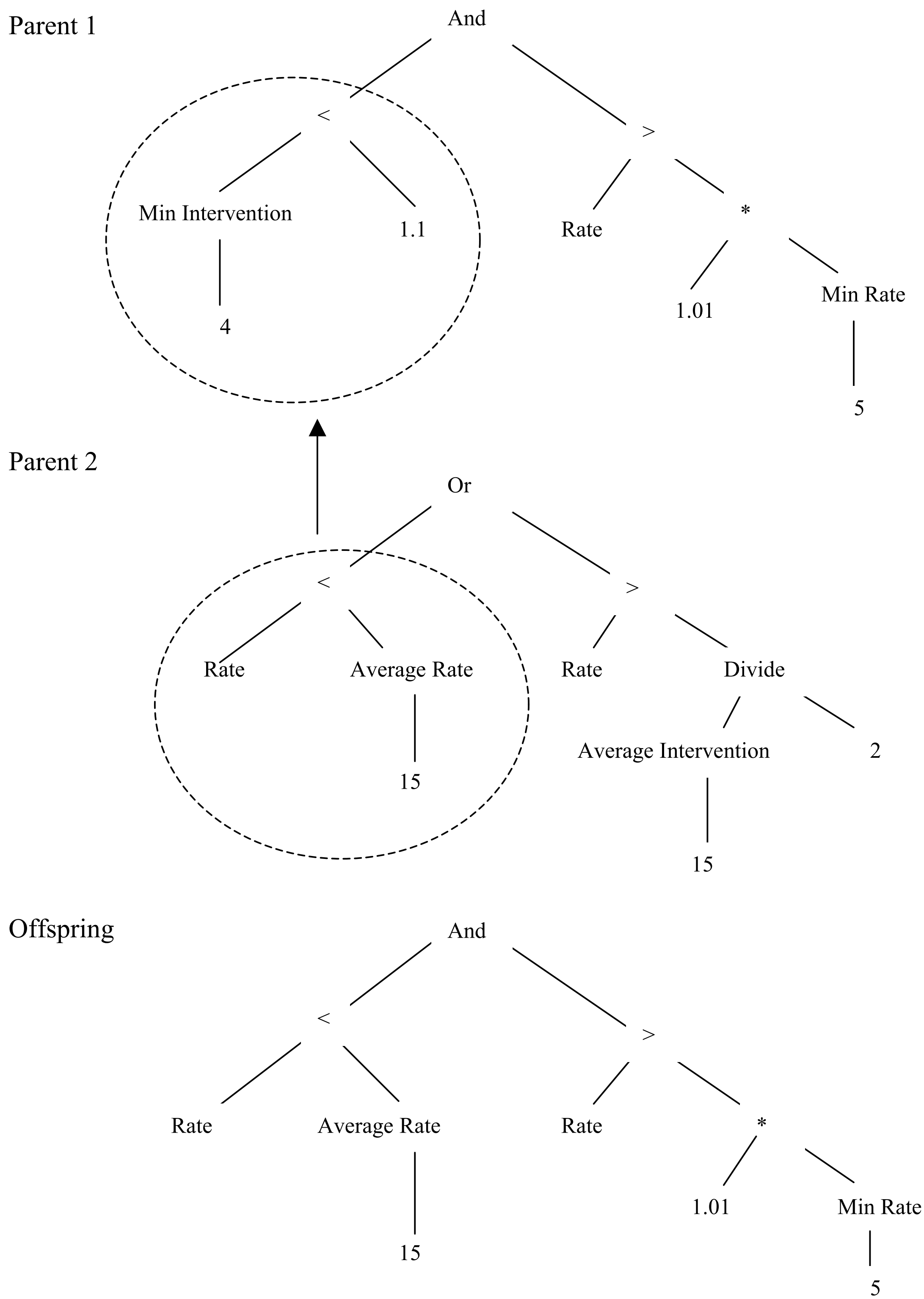
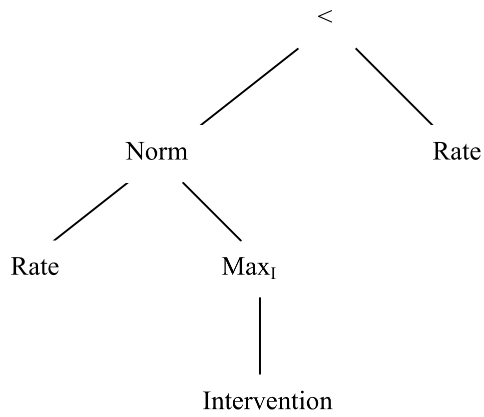


Figure 3 A trading rule for the CHF found by the genetic program



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